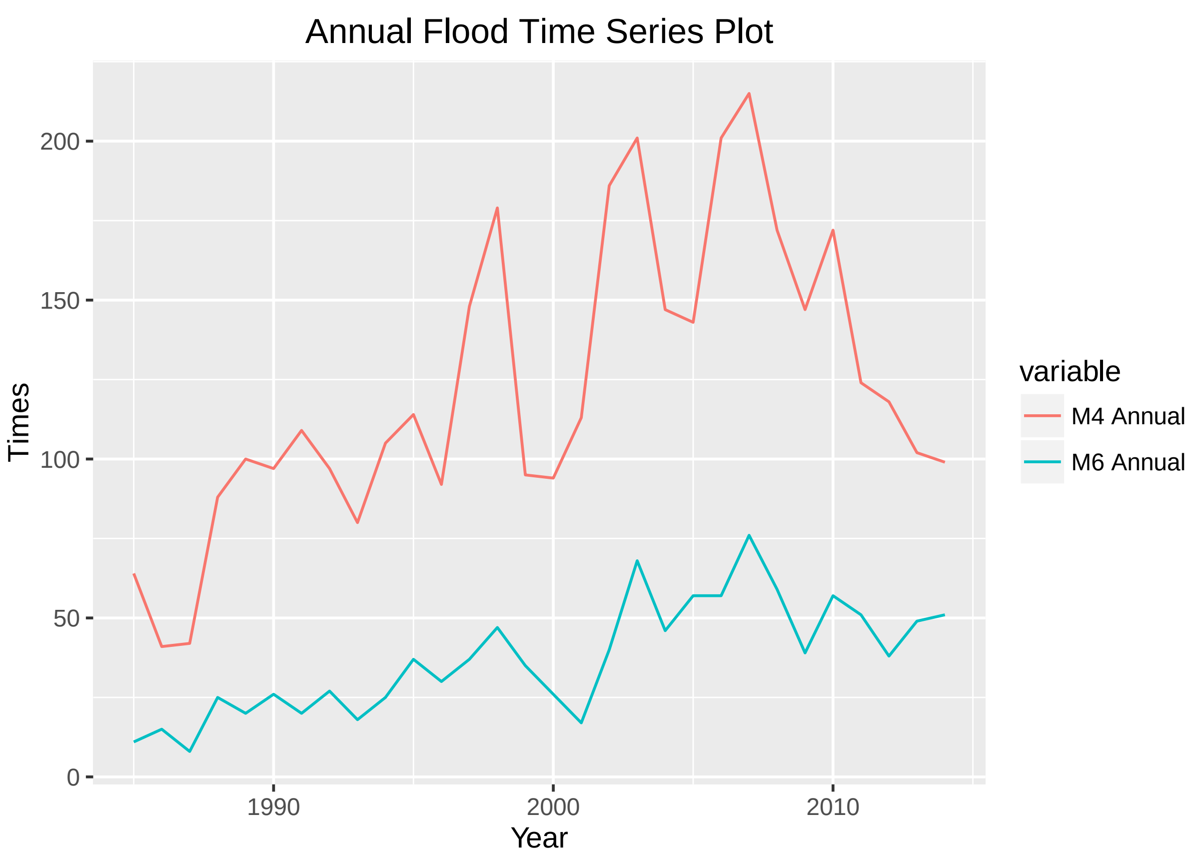
# Proj2

*ggMonet*

*March 3, 2016*

```r
############################
#      Global Setup        #
############################

setwd("/Users/MaxTan/Documents/CU_16spring/EDAV/proj2")


#############################
#  Plots about Flood Stats  #
#############################
stat = read.csv("GlobalFloodsRecordAnalyses.csv", as.is = TRUE)

# Time series plot of annual floods --Xuyan
library(ggplot2)
library(reshape2)
names(stat) = c("Year","M4 Cumulative", "M6 Cumulative", "M4 Annual", "M6 Annual")
floodAnnual = melt(stat[-(2:3)], id.vars = "Year", value.name = "Times")
ggplot(floodAnnual, aes(Year,Times)) + geom_line(aes(color = variable)) +
  ggtitle("Annual Flood Time Series Plot")+scale_fill_brewer(palette="Set2")
```



# TODO 1, scale of the plots and some more variables, and heatmap without geographical info

# all plots in ggplot style

## Tian and Xiyue

```
#####################################
# Plots about Flood Master --Global #
#####################################
master = read.csv("GlobalFloodsRecordMaster.csv", as.is = TRUE)

library(fields)
library(maptools)
library(ggplot2)
library(ggmap)
library(maps)
library(plyr)
library(lattice)
library(Rmisc)
library(mapproj)
library(rgbif)


#Data manipulation --Tian
df = master
df$Centroid.X <- as.numeric(df$Centroid.X)
df$Centroid.Y <- as.numeric(df$Centroid.Y)
df$Severity..<- as.numeric(df$Severity..)
class(df$Centroid.X[1])
```

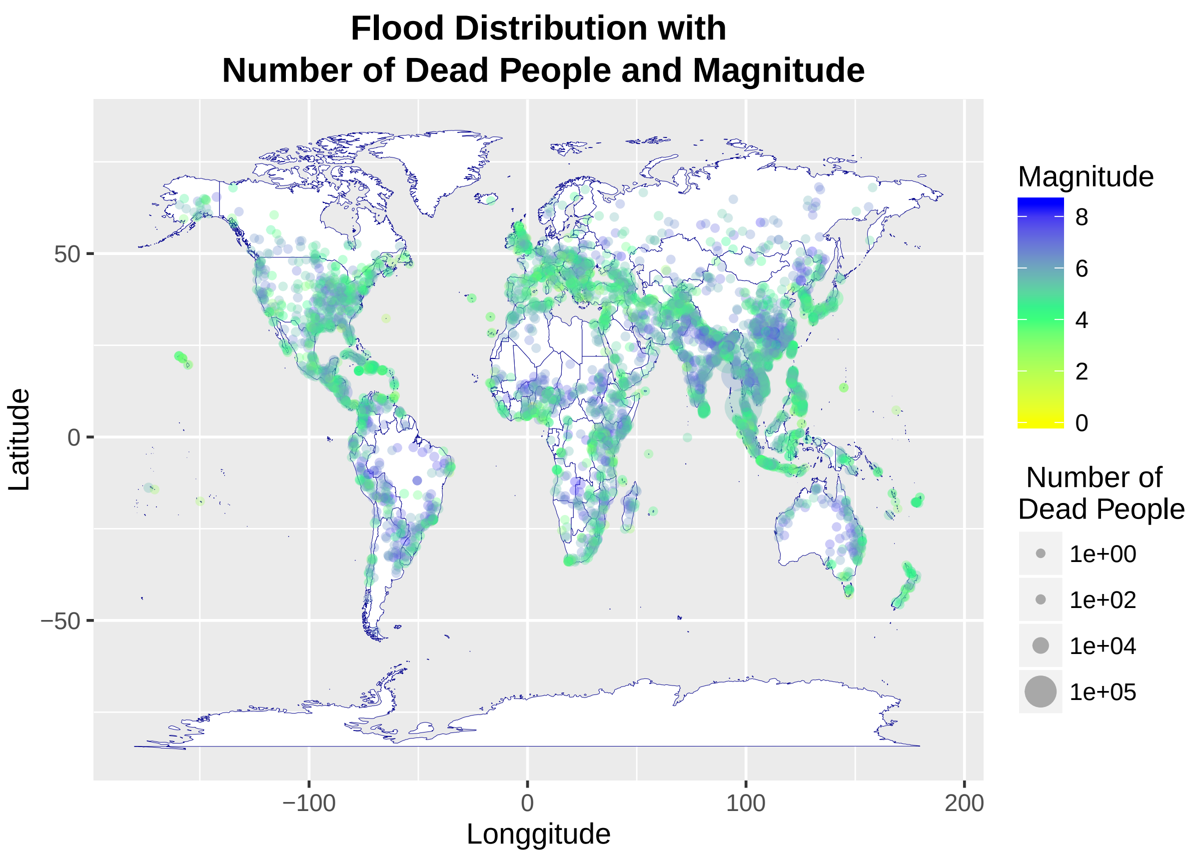
```
## [1] "numeric"
```

```
df <- df[-which(is.na(df$Centroid.X)),]
XLon <- as.numeric(df$Centroid.X)
YLat <- as.numeric(df$Centroid.Y)
Severity <- as.numeric(df$Severity..)
Dead <- as.numeric(df$Dead)
AffectedRange <- as.numeric(df$Affected.sq.km)
Magnitude <- as.numeric(df$Magnitude..M...)
Cause <- df$Main.cause
n <- length(Cause)
```

We preprocessed data by identifying the top 4 main reasons among these 10 causes based on some key words.

```
#Classify top five main causes:
for (i in 1:n){
  if (grepl('eavy',Cause[i])){Cause[i] <- replace(Cause[i], grepl('eavy',Cause[i]),'Heavy Rain') }
  else if(grepl('clone',Cause[i])){Cause[i] <- replace(Cause[i], grepl('clone',Cause[i]),'Tropical Cycl
  else if(grepl('onsoon',Cause[i])){Cause[i] <- replace(Cause[i], grepl('onsoon',Cause[i]),'Monsoon')}
```

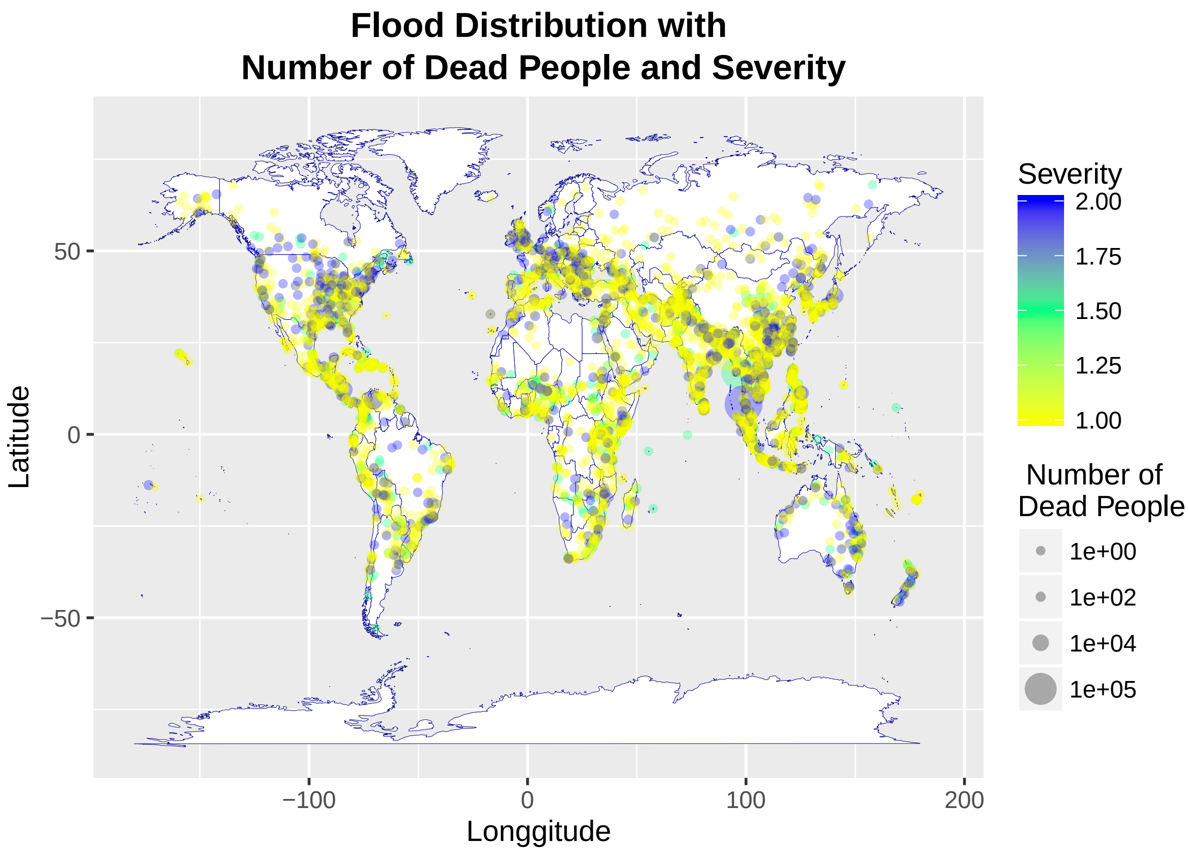
```r
  else if(grepl('orrential',Cause[i])){Cause[i] <- replace(Cause[i], grepl('orrential',Cause[i]),'Torre
  else {Cause[i] <- replace(Cause[i],TRUE,'Other Causes')}
}

#Try ggplot of "Number of Dead People" and "Magnitude" --Tian
df_new1 <- data.frame(XLon,YLat,Magnitude,Dead)
world <- map_data("world")
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_jitter(data=df_new1, aes(XLon, YLat, color = Magnitude , size = Dead ), alpha = 0.3) +
  scale_colour_gradientn(colours = rainbow(3, start = 0.17, alpha = 0.2)) +
  labs(title = "Flood Distribution with\n Number of Dead People and Magnitude", x = "Longgitude",
       y = "Latitude", size = " Number of\nDead People", color = "Magnitude")+
  theme(plot.title = element_text(lineheight=1, face="bold"))+
  scale_size_continuous(breaks = c(1,100,10000,100000))
```



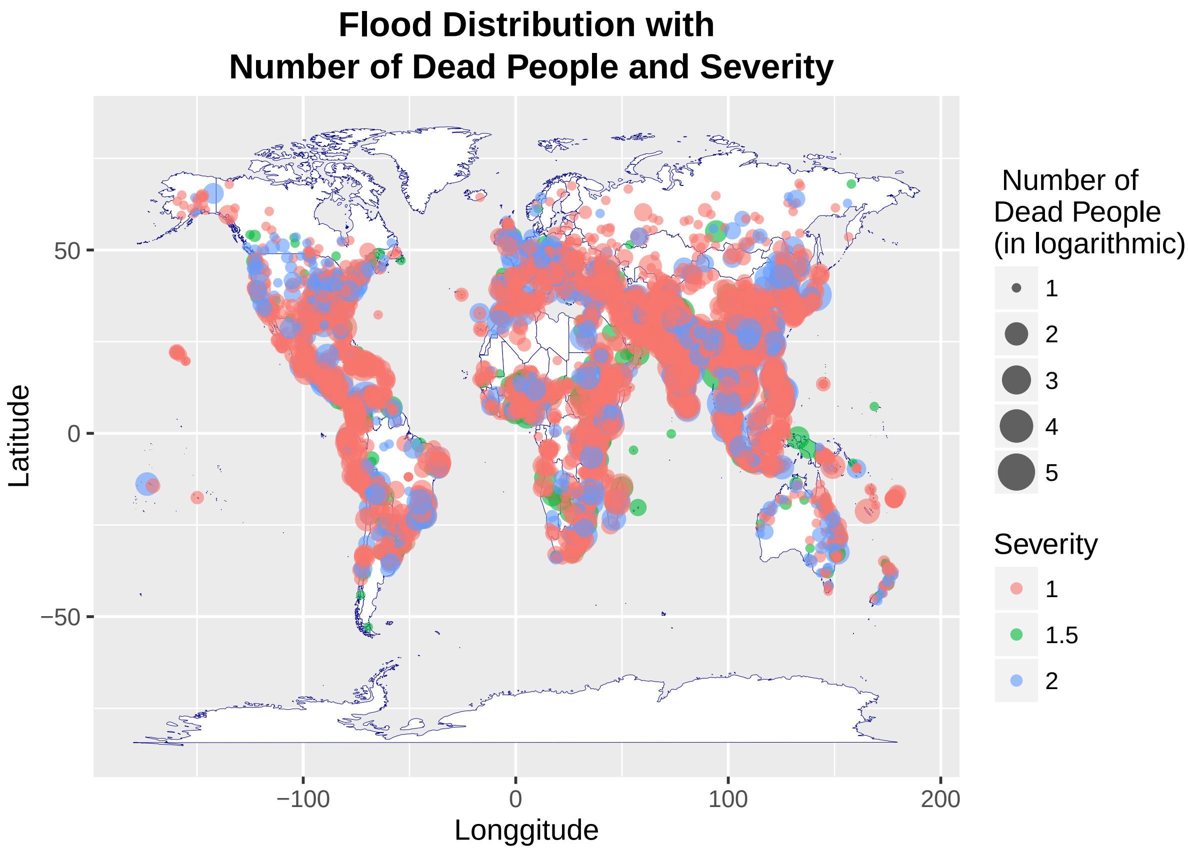

From this distribution plot, combining the magnitude and the number of deaths, we can learn that the floods in East Asia and South Asia had both higher magnitude and larger number of deaths. Specifically, in Malaysia and Thailand, there were several highly serious floods, which resulted in over one hundred thousand people losing their lives. Besides, the East US and Europe also had comparatively more floods with lower magnitude. However, in the southeast coast of South America, the floods suffered from higher magnitudes on average.

```r
#Try ggplot of "Number of Dead People" and "Severity" --Tian and Xiyue
df_new2 <- data.frame(XLon,YLat,Severity,Dead)
world <- map_data("world")
```

```r
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_jitter(data=df_new2, aes(XLon, YLat, color = Severity , size = Dead), alpha = 0.3) +
  scale_colour_gradientn(colours = rainbow(3, start = 0.17, alpha = 0.2)) +
  labs(title = "Flood Distribution with\n Number of Dead People and Severity", x = "Longgitude",
       y = "Latitude", size = " Number of\nDead People", color = "Severity")+
  theme(plot.title = element_text(lineheight=1, face="bold"))+
  scale_size_continuous(breaks = c(1,100,10000,100000))
```

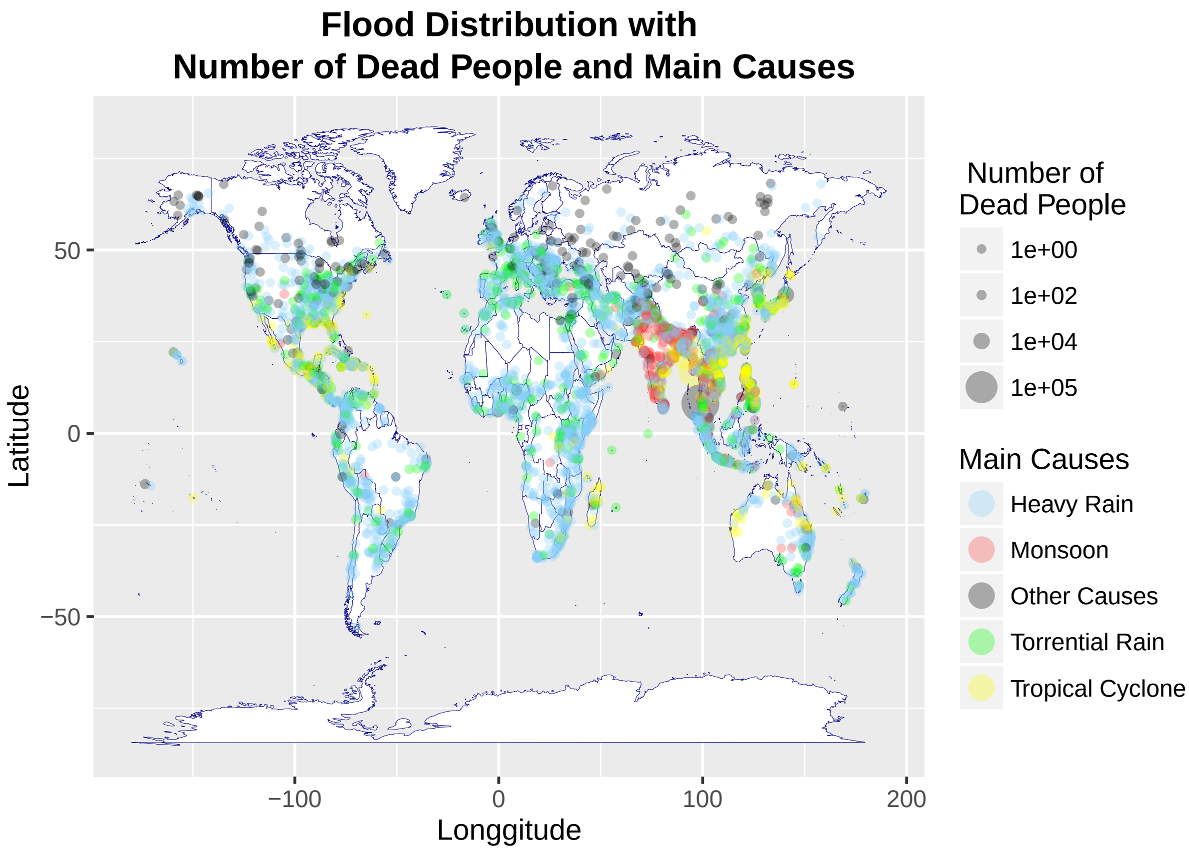



```r
#Try ggplot of "Number of Dead People" and "Severity" another version --Xuyan
# severity as factor and logarithmic dead
Dead <- as.numeric(df$Dead)
df_new <- data.frame(XLon,YLat,Severity,Dead)
df_new$Severity = as.factor(df_new$Severity)
world <- map_data("world")
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_jitter(data=df_new, aes(XLon, YLat, color = Severity, size = log(Dead+10,10)), alpha = 0.6) +
  # scale_colour_gradientn(colours = rainbow(3, start = 0.17, alpha = 0.2)) +
  labs(title = "Flood Distribution with\n Number of Dead People and Severity", x = "Longgitude",
       y = "Latitude", size = " Number of\nDead People\n(in logarithmic)", color = "Severity")+
  theme(plot.title = element_text(lineheight=1, face="bold"))
```

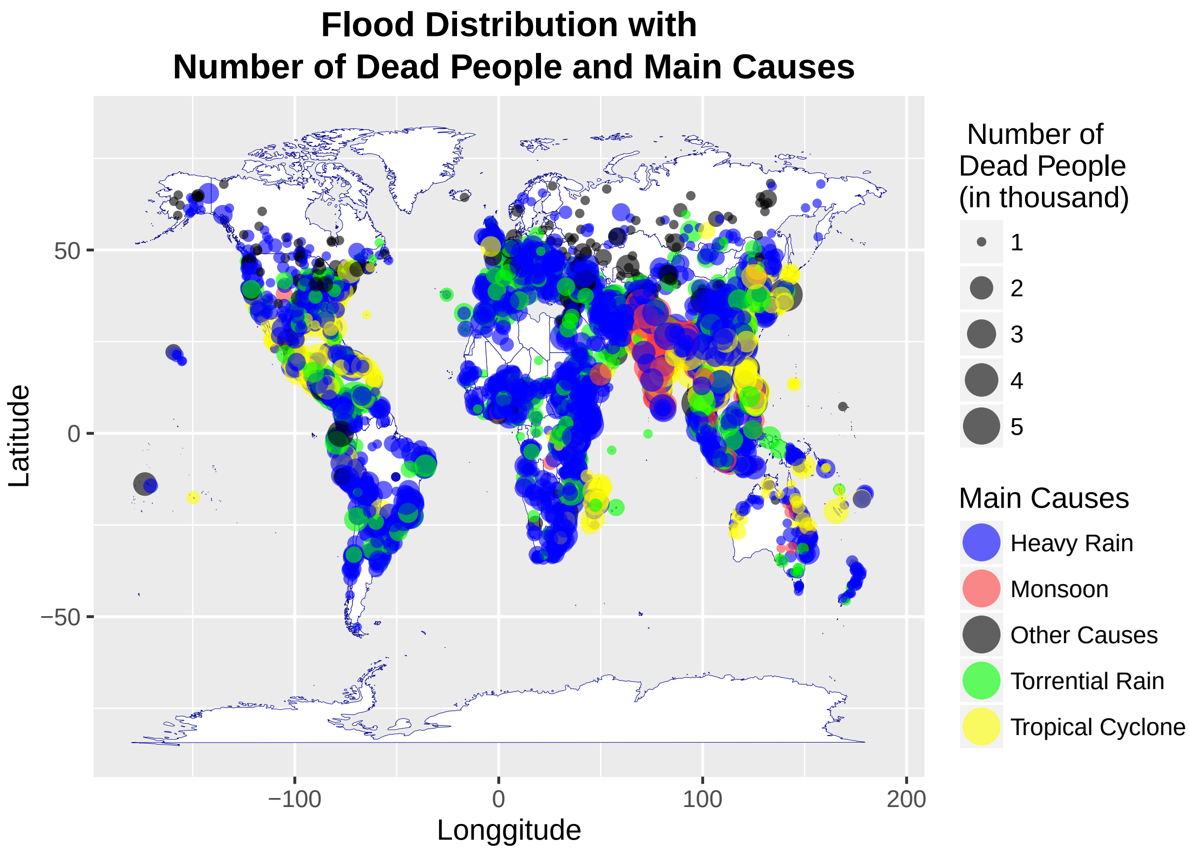



From this distribution plot, combining the severity and the number of deaths, we can see that Europe had the densest floods with high severity. Compared to these, the floods in Asia had higher densities but lower severity. But still, the most serious flood around Malaysia had the most severity and the largest number of deaths at the same time. We also notice that in other places like Russia and Africa, the floods had the lowest severities.

```
#Try ggplot of "Number of Dead People" and "Main Causes" --Tian
df_new3 <- data.frame(XLon,YLat,Cause,Dead)
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_jitter(data=df_new3, aes(XLon, YLat, color = Cause, size = Dead), alpha = 0.3) +
  scale_colour_manual(values = c("lightskyblue","brown1","black","green","yellow"))+
  labs(title = "Flood Distribution with\n Number of Dead People and Main Causes", x = "Longgitude",
       y = "Latitude", size = " Number of\nDead People", color = "Main Causes")+
  guides(colour = guide_legend(override.aes = list(size=4)))+
  theme(plot.title = element_text(lineheight=1, face="bold"))+
  scale_size_continuous(breaks = c(1,100,10000,100000))
```

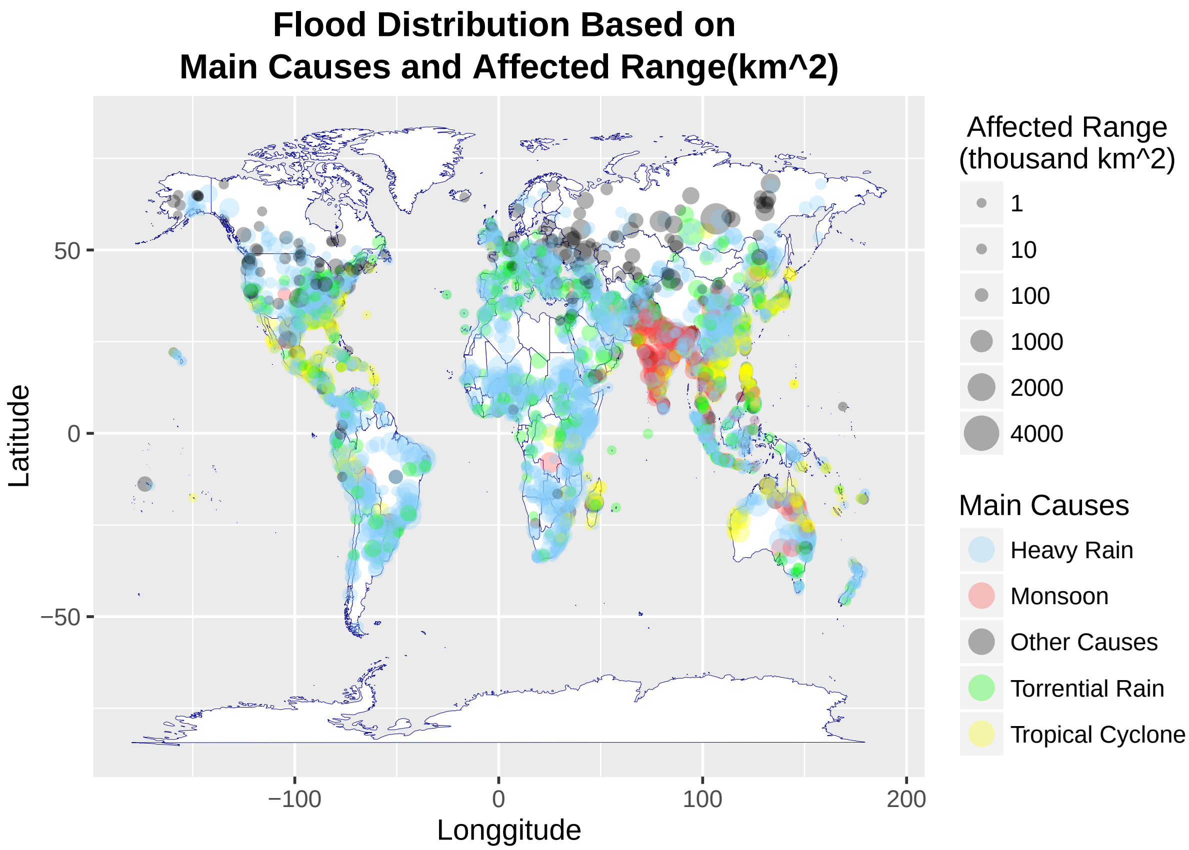



```r
#Try ggplot of "Number of Dead People" and "Main Causes" another version --Xuyan
df_new2 <- data.frame(XLon,YLat,Cause,Dead)
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_jitter(data=df_new2, aes(XLon, YLat, color = Cause, size = log(Dead+10,10)), alpha = 0.6) +
  scale_colour_manual(values = c("blue","brown1","black","green","yellow"))+
  labs(title = "Flood Distribution with\n Number of Dead People and Main Causes", x = "Longgitude",
       y = "Latitude", size = " Number of\nDead People\n(in thousand)", color = "Main Causes")+
  guides(colour = guide_legend(override.aes = list(size=6)))+
  theme(plot.title = element_text(lineheight=1, face="bold"))
```




This time, we analyze the relationship between the main reasons behind these floods and the number of deaths. From the corresponding distribution plot, the following conclusions can be drawn. Firstly, the most common reason in the whole wide world is Heavy Rain, especially in Africa. Then, we find the floods in India mostly resulted from Monsoon, which seems to be the exclusive reason. Besides, the floods cased by tropical Cyclone were concentrated on the South Asia and South US. The dense floods in Europe were caused by a combination of Heavy Rain, Torrential Rain and other reasons. As for the floods in Russia, the reasons behind them seems to be uncommon, at least compared to other places.

```
#Try ggplot of "Affected Range(km^2)" and "Severity"  --Tian and Xiyue
df_new4 <- data.frame(XLon,YLat,AffectedRange,Cause)
world <- map_data("world")
ggplot(world, aes(long, lat)) +
  geom_polygon(aes(group=group), fill = "White", color ="Dark Blue", size = 0.05) +
  geom_point(data=df_new4, aes(XLon, YLat, color = Cause, size = AffectedRange/1000), alpha = 0.3) +
  scale_colour_manual(values = c("lightskyblue","brown1","black","green","yellow"))+
  labs(title = "Flood Distribution Based on \nMain Causes and Affected Range(km^2)", x = "Longgitude",
       y = "Latitude", size = " Affected Range\n(thousand km^2)", color = "Main Causes")+
  guides(colour = guide_legend(override.aes = list(size=4)))+
  theme(plot.title = element_text(lineheight=1, face="bold"))+
  scale_size_continuous(breaks = c(1,10,100,1000,2000,4000))
```



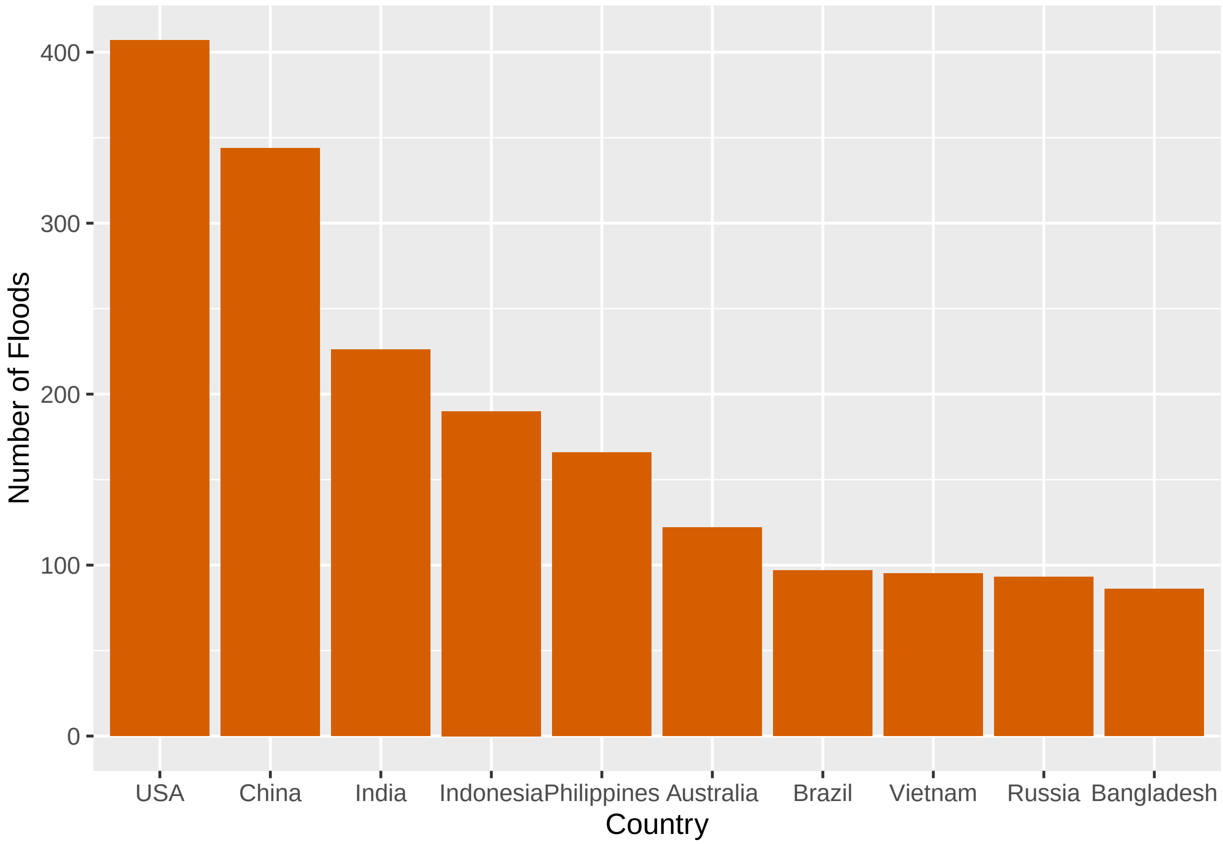

In the end, we compare the distributions between the main causes and the affected range (square kilometer). From the picture, we can see that the floods in India caused by Monsoon seem to have the one of largest affected scopes. Besides, the causes behinds the intensive floods in South Asia were highly complicated, leading to comparatively small affected ranges with surprise. For example, the most terrible flood in Malaysia that we've discussed seems to have an unexpected small range. The situations of East China and East US seem to be similar: large affected ranges and various reasons behind these dense floods. On the top of these coast areas, the floods in Russia mainland also had large affected ranges.

## TODO 2, more plots on the distribution of countries ie density

### Xuyan

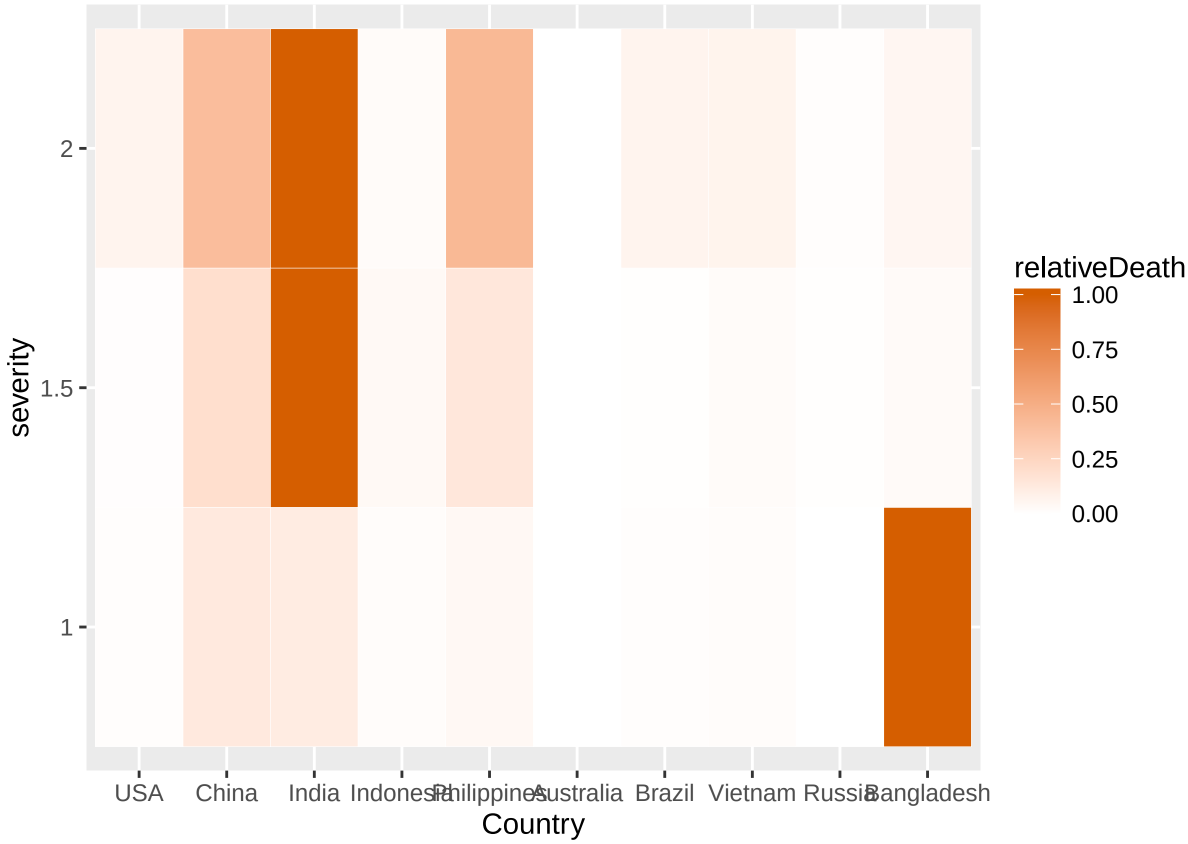
```
###########################
#  Reason for Local Plots #
###########################

# country_cleansing
library(plyr)
country = master
country$Dead = as.numeric(country$Dead)
country = country[!is.na(country$Dead),]

country$Country = gsub("[?]","",country$Country)
country$Country = gsub("[/]","",country$Country)
```

```r
country$Country = gsub("^ ","",country$Country)
country$Country = gsub(" $","",country$Country)
country$Country[country$Country == "USA."] = "USA"


library(dplyr)
library(scales)
country_group = group_by(country,Country)
country_summary = summarize(country_group, num = n(), dead = sum(Dead))
country_summary = as.data.frame(country_summary[order(country_summary$num,decreasing=T),])

ggplot(country_summary[1:10,],aes(reorder(Country,-num),num))+geom_bar(stat = "identity",fill = "#D55E0
  ylab("Number of Floods") + xlab("Country")
```




```r
#List the top3 countries

# heatmap of country + Severity + death
country_sev = group_by(country,Country,Severity..)
country_sev_sum = summarize(country_sev, num = n(), dead = sum(Dead))
names(country_sev_sum)[2] = "severity"

top10 = arrange(country_summary,desc(num))$Country[1:10]
country_sev_top10 = country_sev_sum[country_sev_sum$Country %in% top10,]
country_sev_top10 = ddply(as.data.frame(country_sev_top10), .(severity), transform, relativeDeath = res

p = ggplot(country_sev_top10, aes(reorder(Country,-num),severity)) +
```

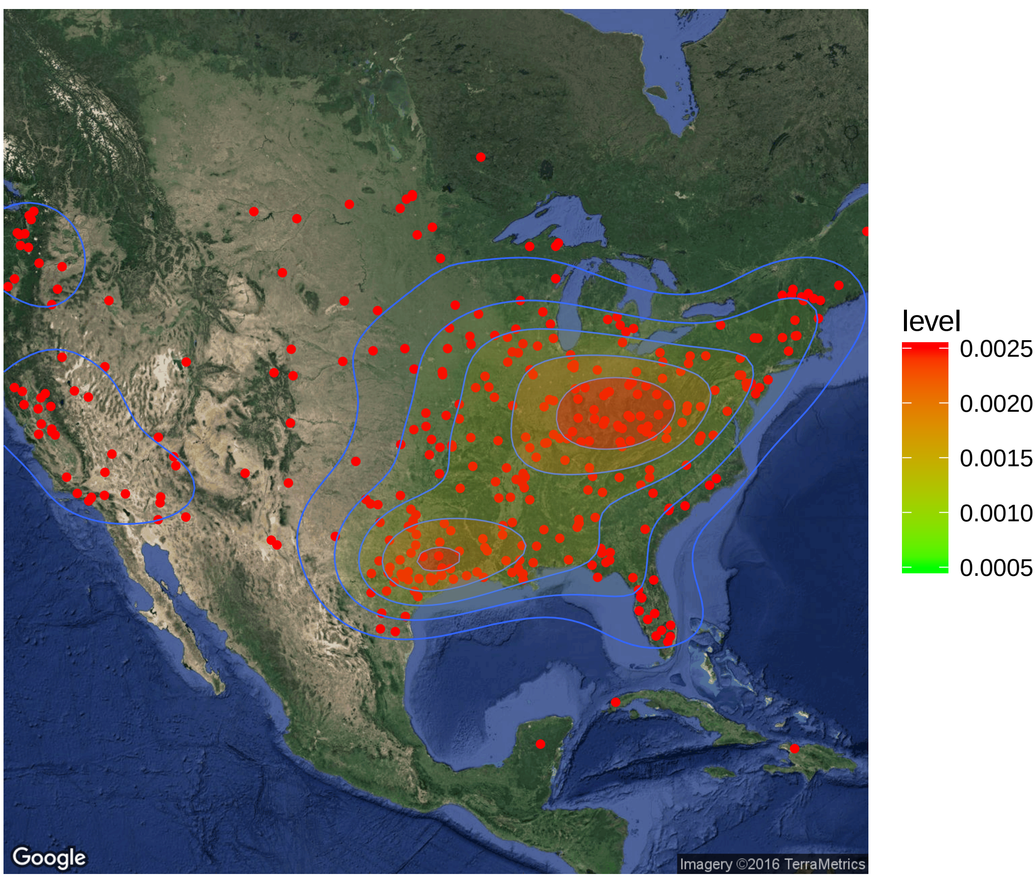
```
        geom_tile(aes(fill = relativeDeath), colour = "white")
p + scale_fill_gradient(low = "white", high = "#D55E00")+
  xlab("Country")
```




As we can see, USA, China and India are the top three frequently impacted countries. In the next part, we will have a more detailed look into the distributions of floods happened in the three countries. And from the heatmap of the relative death (rescaled by the most death occurred in a certain severity), we can see that USA did a great job in preventing death in floods while India and Bangladesh did not.

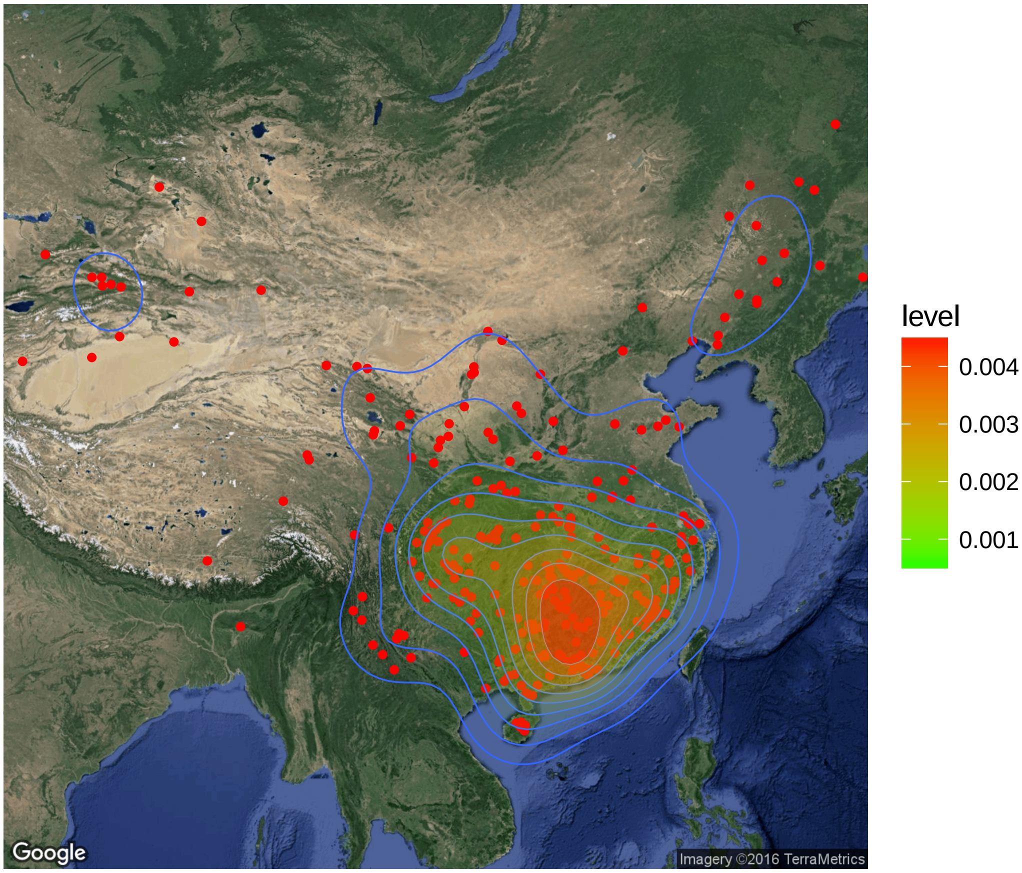
```
#######################################
#  Plots about Flood Master --Local #
#######################################
# -- Hiro

master_f = data.frame(master)


# information of USA


## getting info of usa
usa_master = master_f[master_f$Country == "USA", ]

## getting map of usa
map_usa <- get_map(location = "usa", maptype = "satellite", zoom = 4)
```

```r
## Showing which area had floods in the past
usa_master_heat = data.frame(Centroid.X=as.numeric(usa_master$Centroid.X),
                             Centroid.Y=as.numeric(usa_master$Centroid.Y),
                             Total.floods.M.4=usa_master$Total.floods.M.4)

ggmap(map_usa, extent = "device") +
  geom_point(aes(x=usa_master_heat$Centroid.X,
                 y=usa_master_heat$Centroid.Y),
             data=usa_master_heat, col="red", size=1) +
  geom_density2d(data=usa_master_heat,
                 aes(x = usa_master_heat$Centroid.X,
                     y = usa_master_heat$Centroid.Y),
                 size = 0.3) +
  stat_density2d(data=usa_master_heat,
                 aes(x = usa_master_heat$Centroid.X,
                     y = usa_master_heat$Centroid.Y,
                     fill = ..level..,
                     alpha = ..level..),
                 size = 0.01, geom = "polygon") +
  scale_fill_gradient(low = "green", high = "red") +
  scale_alpha(range = c(0, 0.3), guide = FALSE)
```



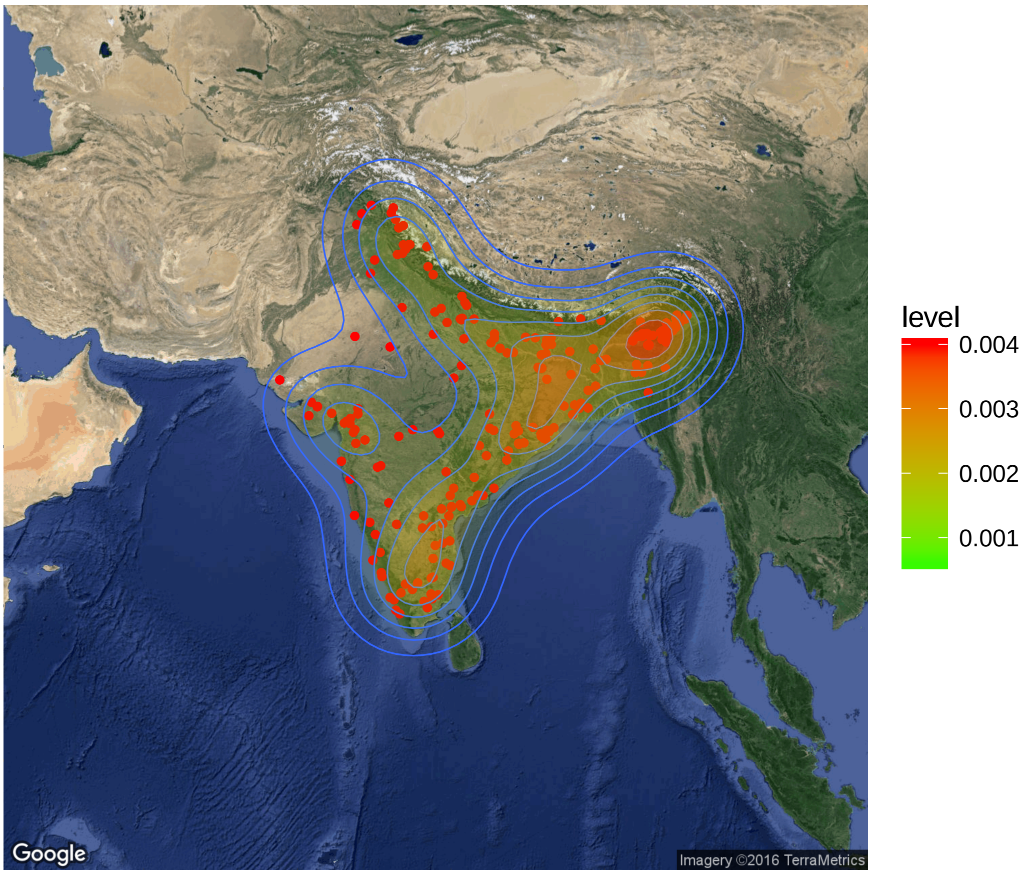

```r
# information of China

## getting info of china
```

```r
china_master = master_f[master_f$Country == "China", ]

## getting map of china
map_china <- get_map(location = "china", maptype = "satellite", zoom = 4)


## Showing which area had floods in the past
china_master_heat = data.frame(Centroid.X=as.numeric(china_master$Centroid.X),
                               Centroid.Y=as.numeric(china_master$Centroid.Y),
                               Total.floods.M.4=china_master$Total.floods.M.4)

ggmap(map_china, extent = "device") +
  geom_point(aes(x=china_master_heat$Centroid.X,
                 y=china_master_heat$Centroid.Y),
             data=china_master_heat, col="red", size=1) +
  geom_density2d(data=china_master_heat,
                 aes(x = china_master_heat$Centroid.X,
                     y = china_master_heat$Centroid.Y),
                 size = 0.3) +
  stat_density2d(data=china_master_heat,
                 aes(x = china_master_heat$Centroid.X,
                     y = china_master_heat$Centroid.Y,
                     fill = ..level..,
                     alpha = ..level..),
                 size = 0.01, geom = "polygon") +
  scale_fill_gradient(low = "green", high = "red") +
  scale_alpha(range = c(0, 0.3), guide = FALSE)
```




```
# information of India


## getting info of India
india_master = master_f[master_f$Country == "India", ]

## getting map of India
map_india <- get_map(location = "India", maptype = "satellite", zoom = 4)

## Showing which area had floods in the past
india_master_heat = data.frame(Centroid.X=as.numeric(india_master$Centroid.X),
                               Centroid.Y=as.numeric(india_master$Centroid.Y),
                               Total.floods.M.4=india_master$Total.floods.M.4)

ggmap(map_india, extent = "device") +
  geom_point(aes(x=india_master_heat$Centroid.X,
                 y=india_master_heat$Centroid.Y),
             data=india_master_heat, col="red", size=1) +
  geom_density2d(data=india_master_heat,
                 aes(x = india_master_heat$Centroid.X,
                     y = india_master_heat$Centroid.Y),
                 size = 0.3) +
  stat_density2d(data=india_master_heat,
                 aes(x = india_master_heat$Centroid.X,
                     y = india_master_heat$Centroid.Y,
                     fill = ..level..,
```

```
                    alpha = ..level..),
                size = 0.01, geom = "polygon") +
  scale_fill_gradient(low = "green", high = "red") +
  scale_alpha(range = c(0, 0.3), guide = FALSE)
```




## TODO 3, plots of some days with a several occurrences and the pressure data

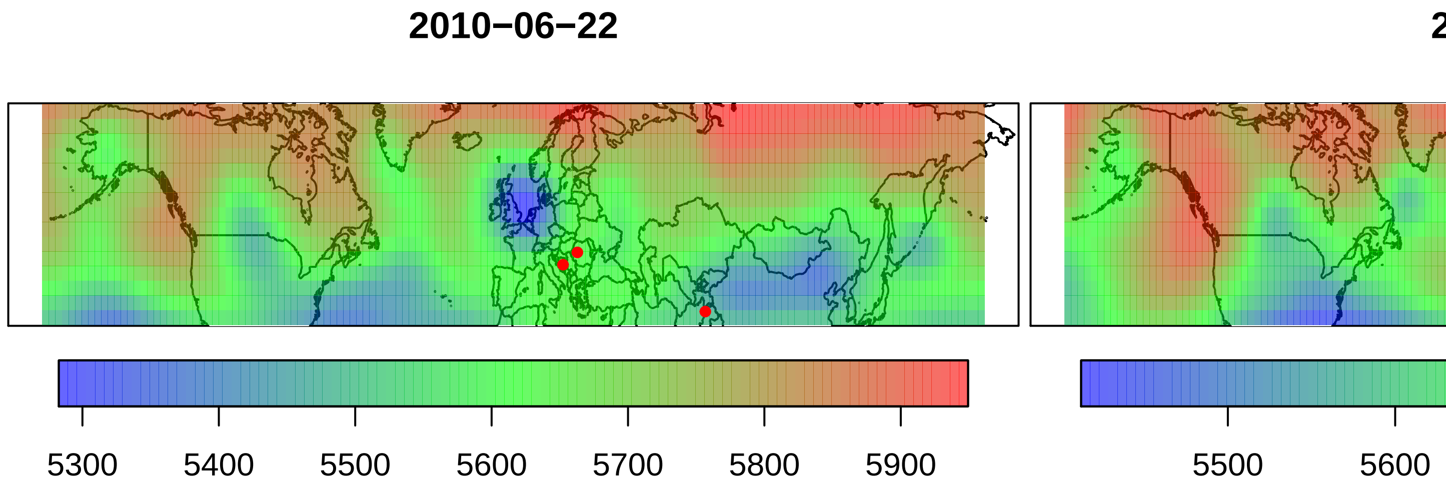
### Xuyan

```
##########################
#  Plots about NOAA Data #
##########################

# Read geological data

library(RNetCDF)
noaa = open.nc('NOAA_Daily_phi_500mb.nc')
data = read.nc(noaa)

xlon = data$X
ylat = rev(data$Y)
```

```
# flood data
# master = read.csv("GlobalFloodsRecordMaster.csv", as.is = TRUE)
# stat = read.csv("GlobalFloodsRecordAnalyses.csv", as.is = TRUE)

master$Began = as.Date(master$Began,format = "%d-%b-%y")
master$Ended = as.Date(master$Ended,format = "%d-%b-%y")

master_phi = master[master$Centroid.Y>min(ylat) & master$Centroid.Y<max(ylat),]

# check the distribution of begin dates
library(dplyr)
date = data.frame(date = master_phi$Began,cnt = 1)
group = group_by(date,date)
summ = summarise(group,cnt = n())
summ$date[summ$cnt == max(summ$cnt)]
```

```
## [1] "2010-06-22" "2010-07-27"
```

```
# found that "1998-05-20" and "2002-06-12" is the most
maxDates = summ$date[summ$cnt == max(summ$cnt)]




# set transparency
add.alpha = function(COLORS, ALPHA){
  if(missing(ALPHA)) stop("provide a value for alpha between 0 and 1")
  RGB = col2rgb(COLORS, alpha=TRUE)
  RGB[4,] = round(RGB[4,]*ALPHA)
  NEW.COLORS = rgb(RGB[1,], RGB[2,], RGB[3,], RGB[4,], maxColorValue = 255)
  return(NEW.COLORS)
}
pal = colorRampPalette(c(rgb(0,0,1), rgb(0,1,0), rgb(1,0,0)))
COLORS = add.alpha(pal(100), 0.6)


for(i in 1:length(maxDates)){
  maxDate = maxDates[i]
  phi3 = as.numeric(maxDate-as.Date("1948-01-01"))+1
  z = data$phi[,,phi3]

  # find the data of the floods that day
  floodDay = master[master$Began==maxDate & is.na(master$Began)==0,]

  # map data
  plot(c(min(xlon)-180,max(xlon)-180), c(min(ylat),max(ylat)), type="n", xlab="", ylab="",xaxt='n',yaxt=
  map(add=TRUE, fill=TRUE, col="white")
  image.plot(xlon-180,ylat,z,add=TRUE, col = COLORS, horizontal = T, legend.mar = 3)
  points(floodDay$Centroid.X, floodDay$Centroid.Y, pch = 20, col = "red")
}
```



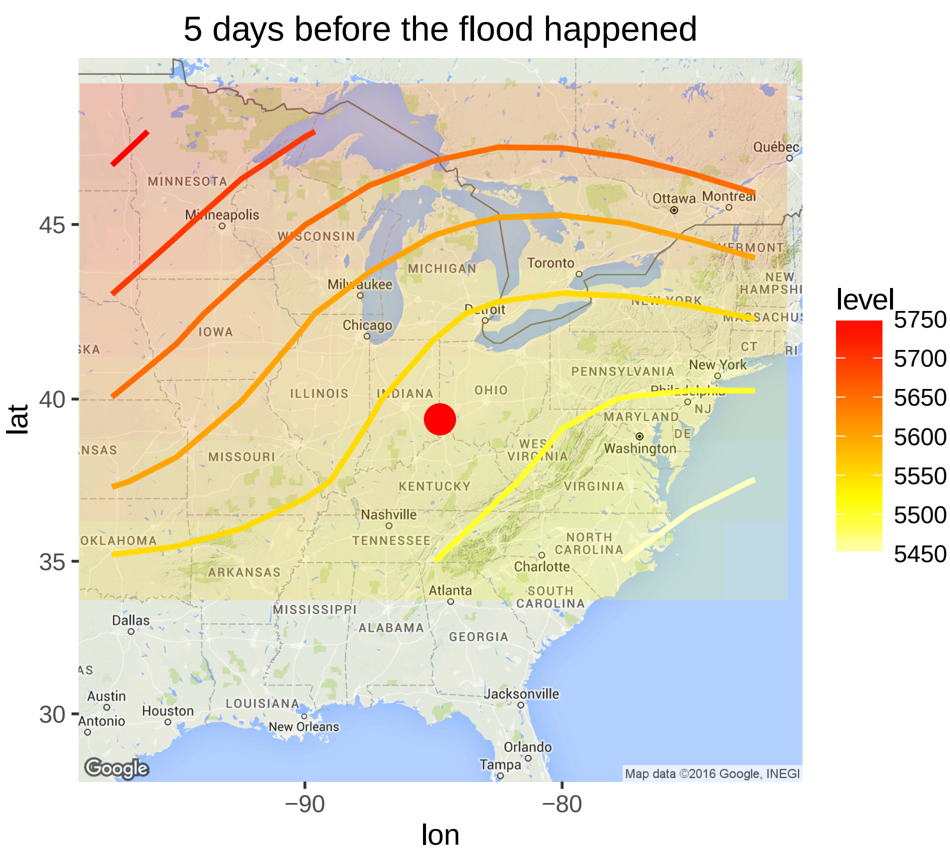

According to the plots, we can see that many floods occurred in the areas with lower pressure, detailed analysis will be illustrated below.

## TODO 4, Countours of a certain flood within the NOAA data area

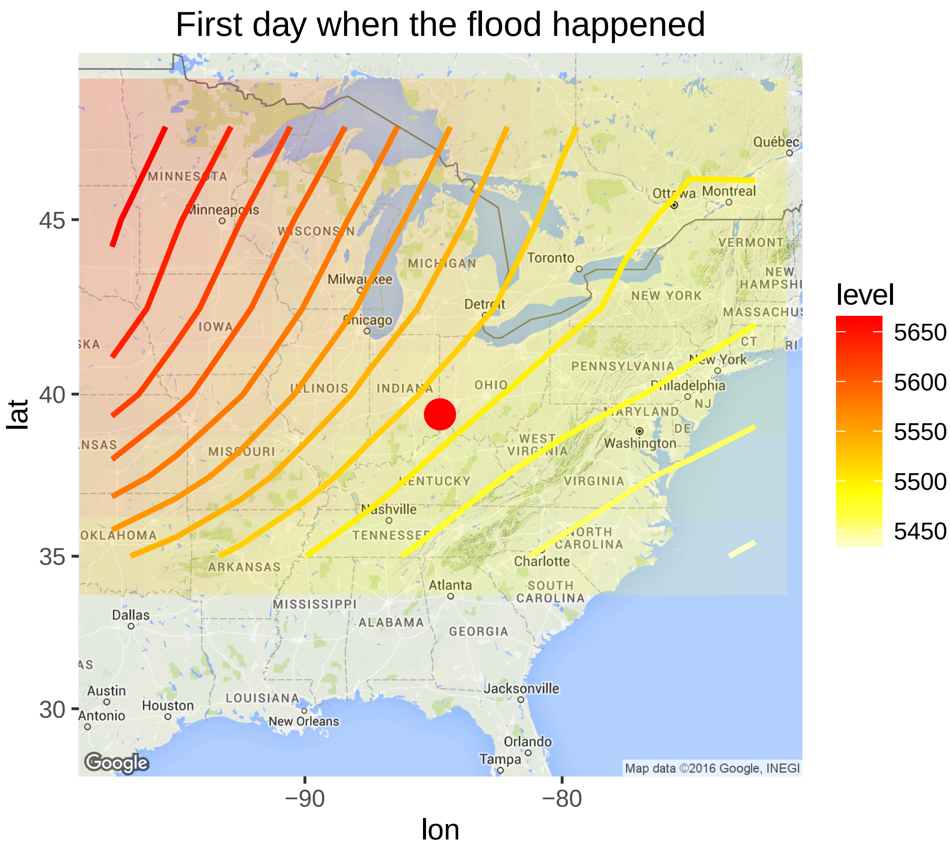
### Hiro, Phoebe

Firstly, we will focus on changes of contours during the flood that happened in the area of Southern Michigan, central Indiana, and western Ohiothe in the US from Jun 27, 2015 to Jun 29, 2015.

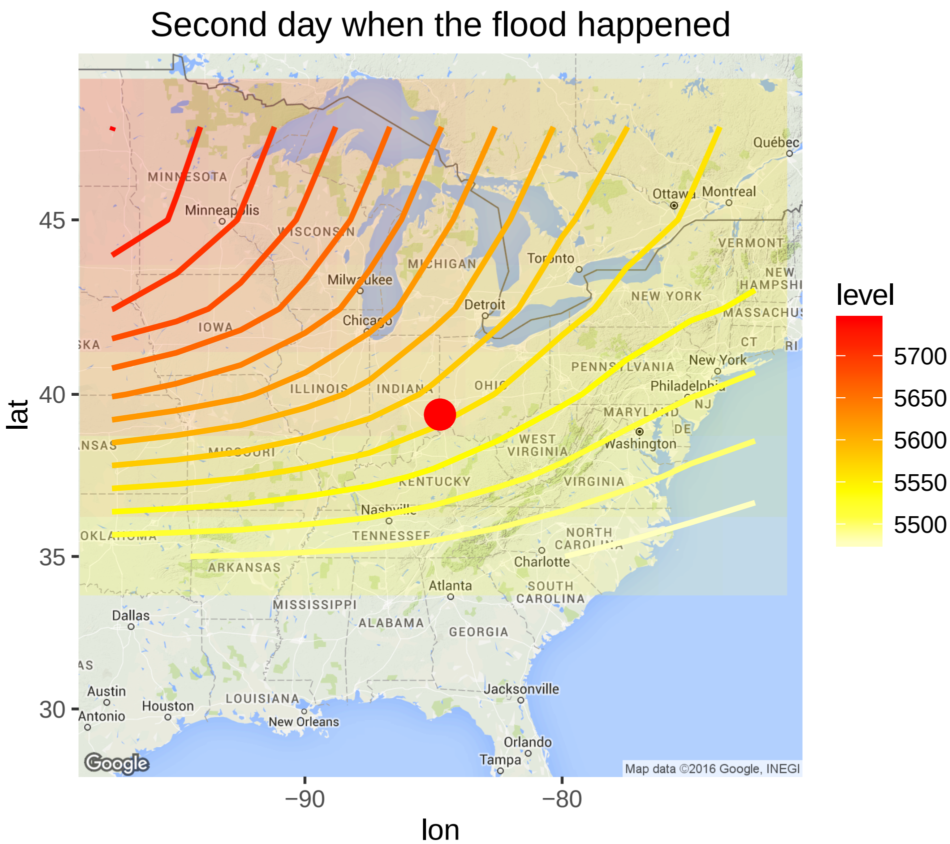
```
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 1, '5 days before the flood happened')
```



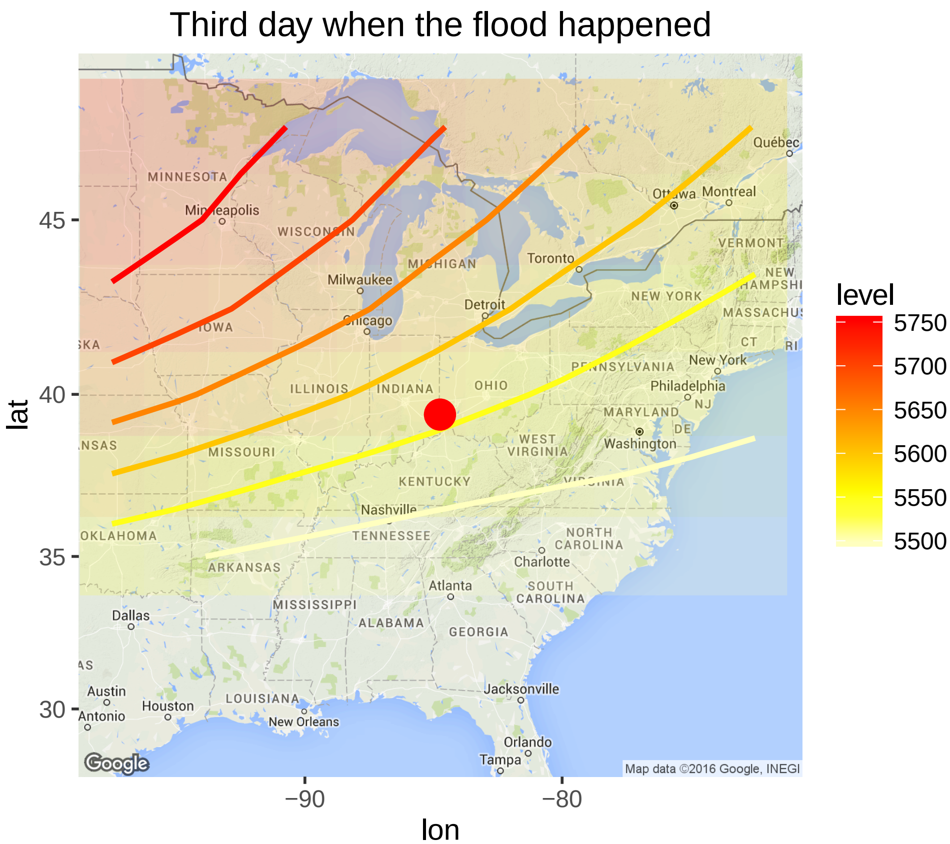
```r
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 6, 'First day when the flood happened')
```



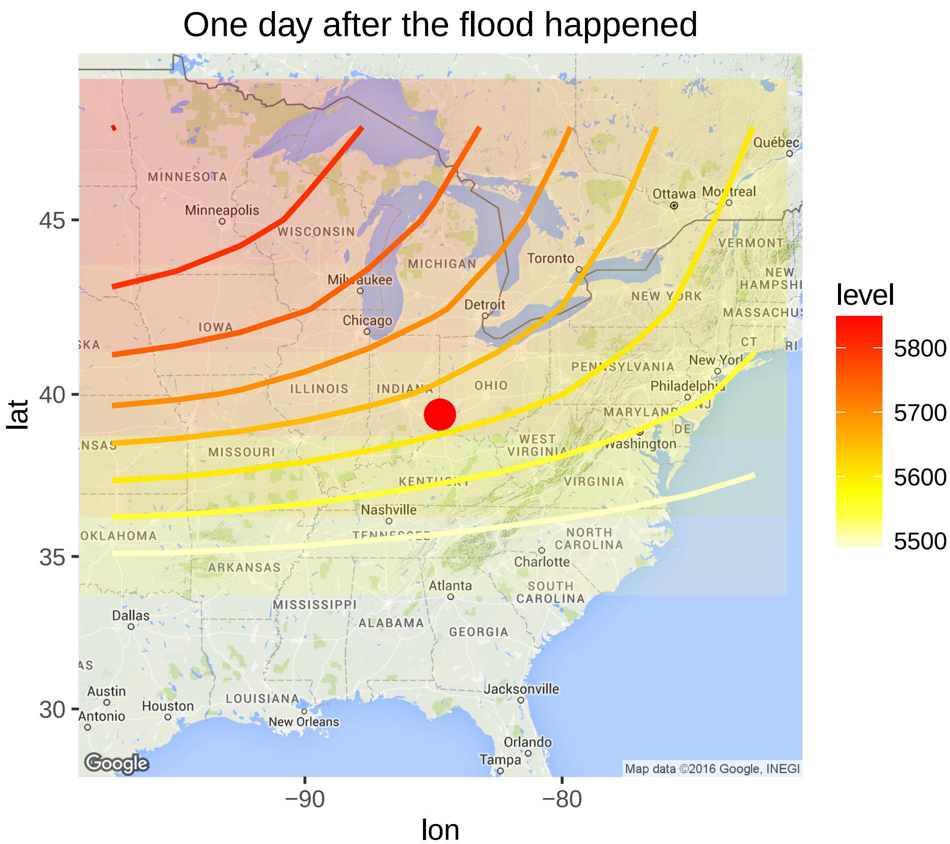

```r
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 7, 'Second day when the flood happened')
```



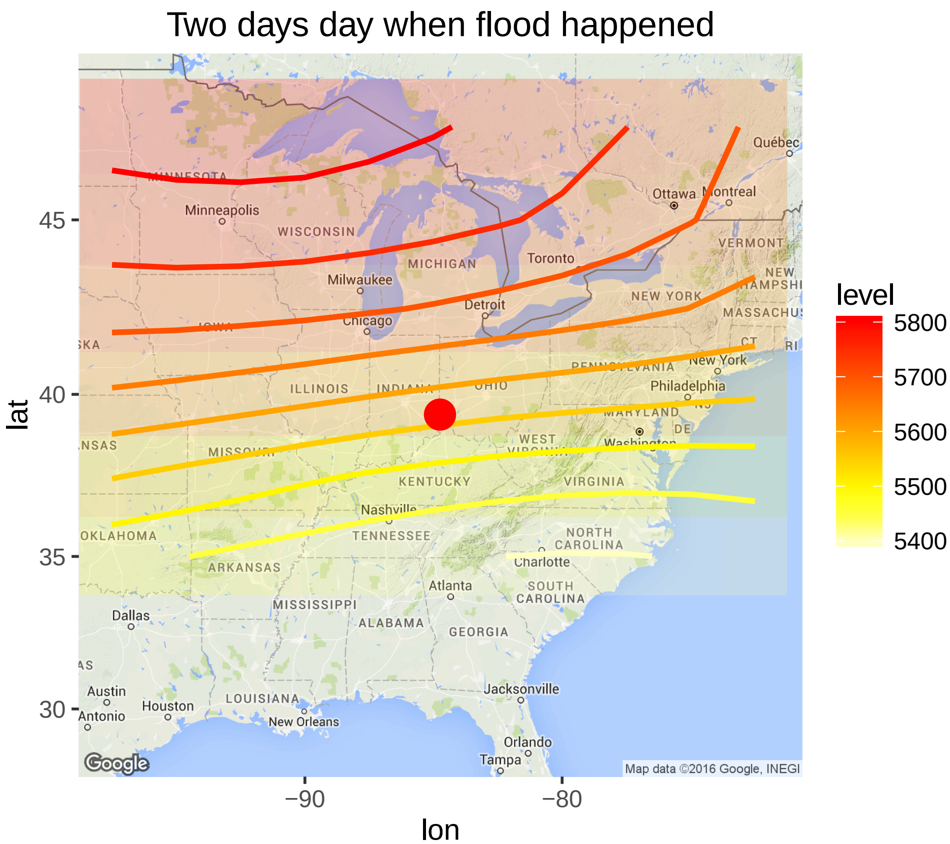

```
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 8, 'Third day when the flood happened')
```



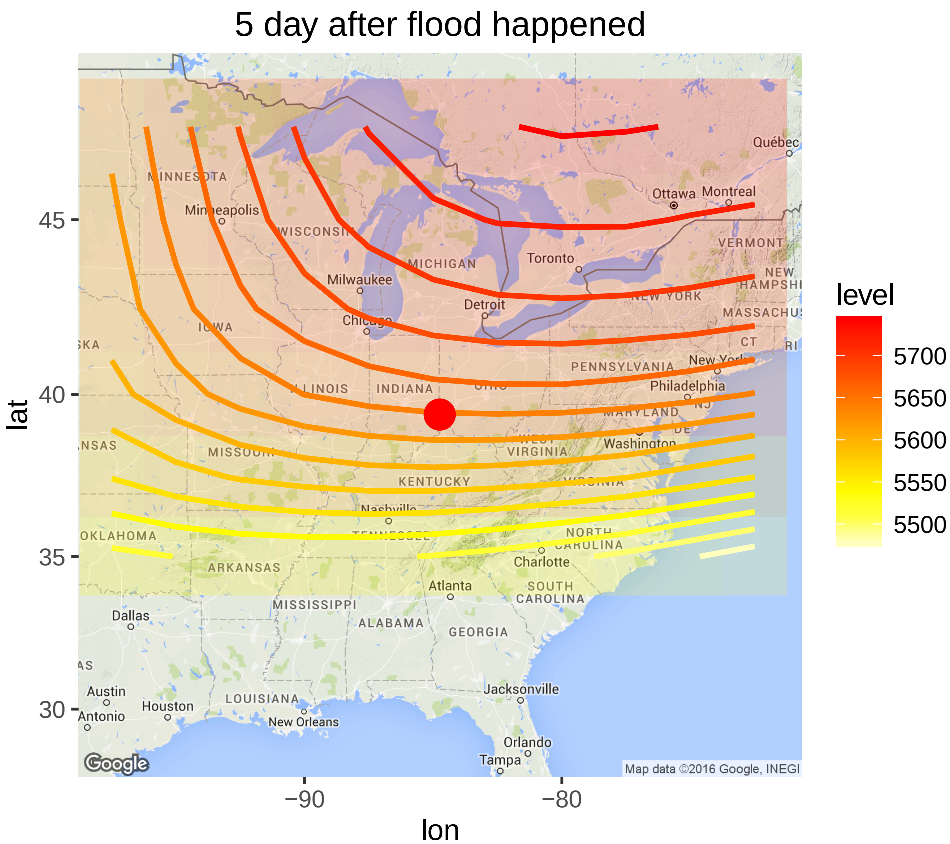

```r
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 9, 'One day after the flood happened')
```




```
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 10, 'Two days day when flood happened')
```




```
draw_map(target, "usa", tmp_xlon, tmp_ylat, tmp_time, 1 + flood_end + 5 - (flood_begin - 5), '5 day afte
```




As seen above, we can see changes of contour when the flood happened. At the second day of the flood, the density of contour is high.

## TODO 5, PCA

### Jordan